Floor Determination in the Operation of a Lift by a Mobile Guide Robot

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Abstract— **Robotic assistants operating in multi-floor buildings are required to use lifts to transition between floors. To reduce the need for environments to be tailored to suit robots, and to make robot assistants more applicable, it is desirable that they should make use of existing navigational cues and interfaces designed for human users. In this paper, we examine the scenario whereby a guide robot uses a lift to transition between floors in a building. We describe an experiment into combining multiple data sources, available to a typical robot with simple sensors, to determine which floor of the building it is on. We show the robustness of this approach to realistic scenarios in a busy working environment.**

I. Introduction

A key challenge facing the adoption of assistive robots is in ensuring they can be integrated into existing environments with the minimum of effort. We are interested in how robots can make use of the wealth of existing information, from human design considerations and infrastructure, to operate within such environments without them being modified and without the need for excessive training.

The ROBO-GUIDE (ROBOtic GUidance and Interaction DEvelopment) project is an interdisciplinary project bringing together engineers and scientists working in computational neuroscience, control systems, formal verification, natural language, and psychology, to address how an assistive robot can be designed and built with a comprehensive view to its requirements. The aim of this project is to develop a guide robot that can navigate inside a large working building, filled with people who are not, on the whole, familiar with robotic technology [1], [2], and to do so in a safe, and reliable way [3]. It will ultimately be tasked with showing visitors around the building and running errands, such as collecting post.

An interesting challenge facing the robot is how it transitions between floors whilst navigating the building. As with other guide robots, our current work employs a wheeled mobile platform (the Pioneer LX), which cannot handle stairs, and so must use lifts to change floors. Prior work in this area has tackled issues relating to identifying and entering a lift [4] [5], identifying and pressing buttons within the lift [6] [7] [8], or using a wireless interface to control the lift [9]. Of particular note is work by Kang et al. [10], which demonstrates mechanisms for both entering and leaving a lift, as well as determining which floor the lift is on by reading the floor indicators.

In this paper we are also concerned with the task of floor determination. However, rather than rely on a single measure (such as the indicator within the lift, which can easily be obscured by other occupants), we are interested in how the robot can make use of the multiple cues available to it, and how it can more confidently estimate its location by combining information from these cues, which may be individually unreliable. This is important in busy environments, where it may not be possible for the robot to get a clear measure from a single source. We therefore examine what sources of information are readily available to the robot and investigate the confidence with which these can be used to determine the floor the robot is on, both individually and when combined, in ideal and non-ideal situations.

In the remainder of this paper, we describe an experiment into how confidently the robot can identify a particular floor from a combination of readily-available human and robotic navigational information. Section II gives details of the robot and its operating environment; Section III discuss timing the motion of the lift, speech recognition of the lift announcements, image processing of the information boards on each floor, localisation confidence and combined floor estimation; Section IV provides experimental results in both favourable and adverse conditions; and finally, we offer some conclusions in Section V.

II. Lift Scenario

ROBO-GUIDE is based on the Pioneer LX platform, a mobile robot equipped with a laser rangefinder and mapping software, sonar and impact sensors, accelerometers, and speech synthesis software. For the guide task, we have also equipped it with a USB microphone, a small camera, and a mobile phone to provide a user interface, Fig. 1. Rather than alter the building infrastructure, we are interested in how the

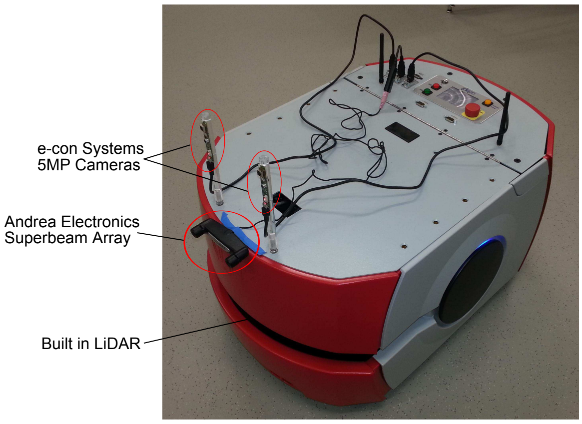

Fig. 1. Pioneer LX platform equipped with cameras an microphone

robot can make use of the existing human-oriented interfaces, and interactions with other building users, to help fulfil its tasks. For example, to operate the lift, the robot will need to request assistance from other lift occupants. However, we are aware that interactions may not always be successful, or trustworthy, and so the robot must be able to determine for itself whether it has arrived and alighted on the desired floor.

In the following experiment, conducted in the Pam Liversidge Building at The University of Sheffield[1], we identify several sources of data available to the robot, which can be used to determine which floor it is on. Each measure can be negatively affected in some way by other building users, and so cannot be relied upon individually. To overcome these detrimental effects, we combine the measurements using a Bayesian filter, and show how the overall localisation confidence is improved in scenarios where measurements are both near-to and far-from ideal.

III. Floor Detection

A. Transit time

Upon entering the lift, the robot measures how long it is in motion and uses this to estimate how many floors have been transited. The measurement of transit time uses a number of triggers such as vertical acceleration, air pressure change and the opening and closing of the doors to start and stop the timer at the appropriate moment. Unfortunately, the transit time for a given number of floors is not constant, but depends on factors such as the occupancy of the lift. A number of data sets were collected to determine a mean transit time which the robot can compare its measurement to in order to produce a Probability Mass Function (PMF).

For the lift in the Pam Liversidge Building, the following relationships were determined

$$\bar{t}_{transit}(n) = \begin{cases} 5 + 2.3n & \text{if } a_{peak} > 0 \\ 9 + 0.85n & \text{otherwise} \end{cases} \tag{1}$$

where $\bar{t}_{transit}$ is the mean time (in seconds) the lift spends in motion, n is the number of floors transited and $a_{peak} > 0$ signifies positive vertical acceleration indicating the lift is going up.

A time measurement from the robot (t) is compared with (1) to produce a PMF indicating the probability of having transited a certain number of floors

$$P(\text{Floors Transited} = i) = \frac{1}{\rho}|\bar{t}_{transit}(i) - t|^{-1} \tag{2}$$

where ρ is a normalisation term given by

$$\rho = \sum_{i=1}^{N-1} |\bar{t}_{transit}(i) - t|^{-1} \tag{3}$$

where N is the total number of floors. The distribution used above requires no additional parameters (such as variance), thus simplifying the implementation. It does, however, suffer from a singularity should any of the measured times precisely match the mean. This is mitigated by testing for this condition before the calculation of $P(\text{Floors Transited} = i)$ and assigning it to unity if necessary.

B. Speech recognition

The robot records audio in the lift using a low-budget USB far-field microphone, the Andrea External USB Soundcard/SuperBeam Microphone Bundle[2], with a sample rate of 44.1kHz and 16-bit precision. The floor announcements are the only in-lift measure of floor available because the visual indication is high mounted and out of view of the robots cameras.

We used audio collected for a previous study [1] as training data for this experiment. The recognition system was built using the Kaldi toolkit [11], using the SGMM decoding approach [12]. The acoustic models were trained on the WSJ British English spoken corpus. We used the speaker adaptation (SAT) scripts to adapt the models to the acoustic conditions of the lift. The pronunciation dictionary was designed to fit the phrases uttered by the lift, and the language model was created as a constrained grammar to only allow the phrases that are uttered by the lift.

The confidence distribution for each announcement was determined using the acoustic model scores for the n-best list generated by the recogniser. In the previous study we found an accuracy of 55% for the identification of floor announcements. We used this figure to weight the values appropriately for the combined measures.

[1] In the Pam Liversidge Buidling floors are alphabetically labelled, from the ground up, and include floor ‘C+’ due to a neighbouring mezzanine level

[2] http://www.andreaelectronics.com/

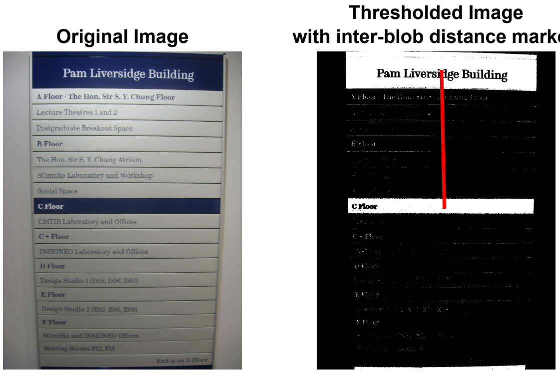

Fig. 2. Detection of the C floor information board

Fig. 3. Calculating localisation score by comparing laser rangefinder data (black) to (a) the correct floor map (grey), (b) an incorrect floor map

C. Vision processing

There is an information board outside the lift on each floor of the Pam Liversidge Building, shown to the left of Fig. 2. The robot captures an image of the board as soon as the lift doors open, enabling it to decide whether or not it should leave the lift based on the combined estimation technique discussed in Section III-E. Due to distance of the board from the lift and the relatively low camera resolution it is not possible for the robot to read the text via an Optical Character Recognition (OCR) technique. Instead, the distance between the two blue bars, indicating the building and current floor respectively, is correlated with each floor.

Fig. 2 illustrates the process of floor detection based on an image of the information board. Firstly, the image is thresholded in the Hue-Saturation-Value (HSV) colourspace to isolate the blue areas as a binary image. This thresholded image is then passed to a blob-analysis routine which calculates the area and centroid position of the two largest blobs. The distance between the blobs is then calculated as

$$d_{scaled} = \frac{d_{centroid}}{\sqrt{A_{largest}}} \tag{4}$$

where $d_{centroid}$ is the Euclidean distance between the centroids and $A_{largest}$ is the area of the largest blob. This scaling ensures the algorithm is insensitive to the size of the information board in a given image.

Finally, the scaled distance is compared with reference values for each floor to produce a PMF

$$P'(\text{Floor} = i) = \frac{1}{\tau}|d_i - d_{scaled}|^{-1} \tag{5}$$

where d_i is the reference distance of the ith floors information board and τ is a normalisation term similar to (3)

$$\tau = \sum_{i=1}^{N} |d_i - d_{scaled}|^{-1} \tag{6}$$

An additional check of the angle between the line joining the two centroids and vertical (θ_{blobs}) is performed in order to discount erroneous images, such as when the board is occluded by a person. Therefore the final vision based PMF is

$$P(\text{Floor}) = \begin{cases} P'(\text{Floor}) & \text{if } \theta_{blobs} < 10^o \\ \mathcal{U}(1, N) & \text{otherwise} \end{cases} \tag{7}$$

where $\mathcal{U}(1, N)$ is the uniform distribution over the integer interval $[1, N]$.

D. Mapping

Before the experiment, we used the onboard laser scanner and inbuilt software (MobileEyes, Mapper 3, and ARNL Server) to map the 7 floors of the building. A measure of confidence of which floor the robot is on was generated by comparing the laser point cloud data from the robot with the pre-recorded maps of each floor, see Fig. 3. Unlike the previous measures, however, it is necessary for the robot to leave the lift before it can detect differences in the layout of the various floors, as the areas immediately adjacent to the lift are identical. Therefore, this measure is only taken as a final check that the robot has left the lift on the correct floor.

E. Combined floor estimation

The previous sections have detailed processes for obtaining PMFs from various sensors, indicating the confidence of the robot being on a particular floor. These measurements are combined using a Bayesian filter to produce a final estimate of the robots position.

Initially the robot has some confidence that it is on a particular floor, $P(\text{Initial Floor})$. This is likely to be a degenerate distribution $P(\text{Initial Floor} = i) = 1$, meaning the robot knows it starts on floor i. Alternatively, if the robot is completely lost it may be the uniform distribution $P(\text{Initial Floor}) = \mathcal{U}(1, N)$, where N is the number of floors.

Upon entering the lift, the robot is able to detect which direction it is travelling and measures the transit time PMF as discussed in Section III-A. This PMF, $P(\text{Floors Transited})$ is then used to predict which floor the robot is on, using the following process for $i = 1...(N-1)$

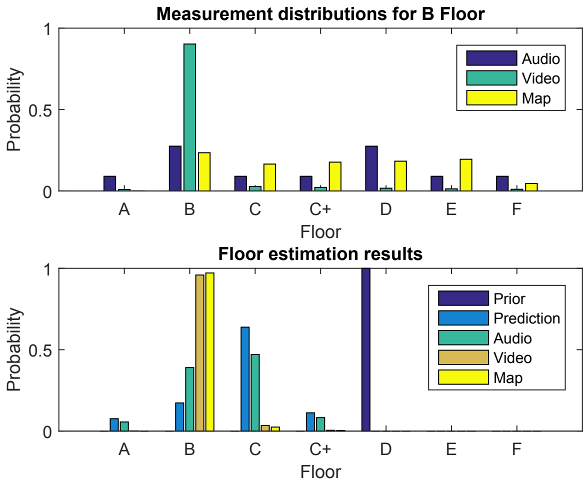

Fig. 4. Prediction of the current floor by the robot. Initially located on D floor, travelling to B floor

1) Shift the values of the $P(\text{Initial Floor})$ PMF by i elements, to the right if the lift is going up, otherwise to the left
2) Discard the out of range elements and fill the leftmost (or rightmost) elements with zeros
3) Multiply by $P(\text{Floors Transited} = i)$
4) Sum these distributions to build up $P'(\text{Floor}|\text{Transit})$

This process discards some information from the $P(\text{Initial Floor})$ corresponding to infeasible combinations of initial floor and transit (such as being on the top floor of a building, then going up 3 floors), leading to a non-unity sum. To recover a correct PMF simply divide by a normalisation term

$$P(\text{Floor}|\text{Transit}) = \frac{1}{\alpha} P'(\text{Floor}|\text{Transit}) \tag{8}$$

where α is a normalisation term.

Finally, incorporate successive measures of the floor by sequential application of Bayes theorem

$$P(\text{Floor}|\text{Transit}, \text{Audio}) = \frac{1}{\beta} P(\text{Audio}|\text{Floor}) P(\text{Floor}|\text{Transit}) \tag{9}$$

$$P(\text{Floor}|\text{Transit}, \text{Audio}, \text{Video}) = \frac{1}{\gamma} P(\text{Video}|\text{Floor}) P(\text{Floor}|\text{Transit}, \text{Audio}) \tag{10}$$

$$P(\text{Floor}|\text{Transit}, \text{Audio}, \text{Video}, \text{Map}) = \frac{1}{\delta} P(\text{Map}|\text{Floor}) P(\text{Floor}|\text{Transit}, \text{Audio}, \text{Video}) \tag{11}$$

where β, γ and δ are normalisation terms.

Fig. 4 shows an example of the calculations detailed above, for a robot initially located on D Floor, travelling to B Floor. The top plot shows each of the measurement distributions $P(\text{Audio}|\text{Floor})$, $P(\text{Video}|\text{Floor})$ and $P(\text{Map}|\text{Floor})$. The robot knows it is initially on D Floor, therefore $P(\text{Initialy Floor} = \text{D}) = 1.0$, this **prior** distribution can be seen in the bottom plot.

The bottom plot in Fig. 4 illustrates each step of the estimation detailed above. The second set of bars show the **prediction** distribution $P(\text{Floor}|\text{Transit})$. Due to the variable nature of the transit times, the maximum prediction probability is C Floor. Incorporation of the audio measurement $P(\text{Audio}|\text{Floor})$ in the third set of bars, leaves a roughly equal chance of being on Floors B or C. Incorporating the video distribution in the fourth set of bars gives the robot a high enough confidence ($> 90\%$) of being on B floor that it will leave the lift and progress to perform the map measurement. Finally. incorporating the map measurements in the final set of bars gives the robot a 97% confidence of being on B Floor. If the confidence had gone down significantly upon taking the map measurement the robot would be sent back to the lift to re-acquire the video image and if necessary re-enter the lift.

IV. Experimental results

In order to test the performance of the floor estimation techniques discussed above, the robot was operated in the lift a number of different times each with a different level of complexity. Initial tests were performed in favourable conditions, without any people or obstructions in the environment to interfere with the measurements. A more complex series of tests were conducted in which the robot was operated in adverse conditions, with the addition of people and objects in the environment.

A. *Favourable conditions*

A number of tests in favourable conditions were performed and this section presents the results from one of these tests. Fig. 5 illustrates the measurement probabilities obtained from operating the actual robot in the lift without any additional obstacles. It is clear that the audio measurement is reasonably poor at distinguishing the correct floor, even in favourable conditions, due to the low volume of the announcements and background noise from the lift itself. The audio measurement was still included in this experiment as it provides an initial estimate of the floor before the lift doors have actually opened. The video measurement provides a very distinct indication of the correct floor whilst the map measurement struggled to differentiate floors B-E due to the similarity of their layout.

For each floor in Fig. 5, the robot was initially located on another random floor. Assuming the robot knows its starting floor with certainty, the Bayesian filtering technique detailed in Section III-E is applied. Fig. 6 illustrates the floor prediction after only measuring the transit time and Fig. 7 illustrates the combined floor estimate, which is clearly a significant improvement over transit time and any single measurement from Fig. 5.

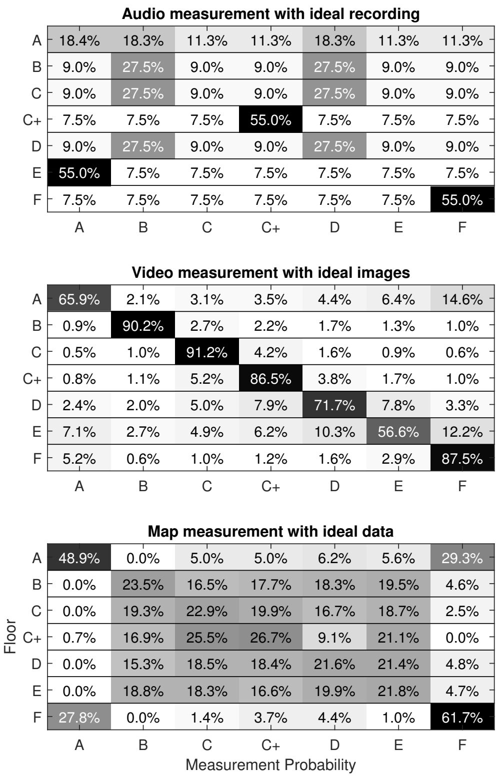

Fig. 5. Measurement probabilities in favourable conditions

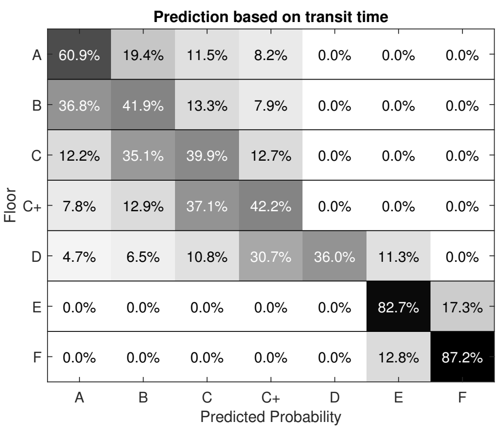

Fig. 6. Floor prediction based on transit time

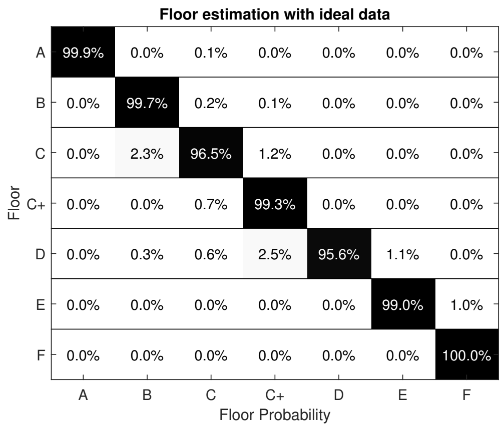

Fig. 7. Floor estimate in favourable conditions

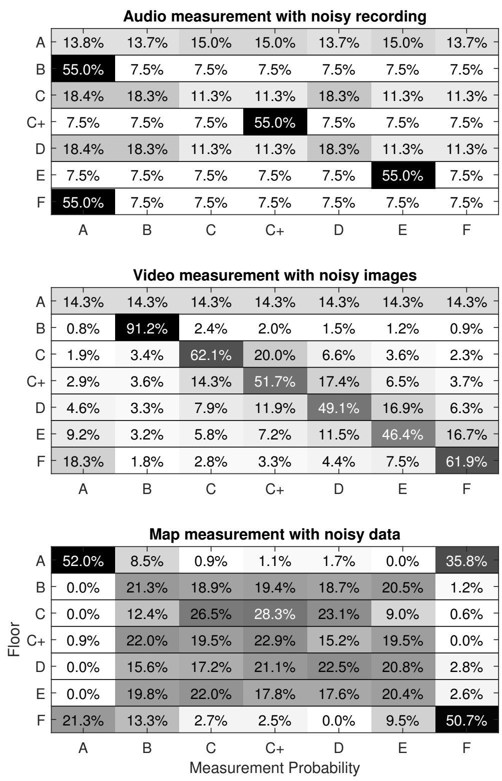

Fig. 8. Measurement probabilities in adverse conditions

B. Adverse conditions

Fig. 8 illustrates the measurement probabilities calculated from noisy data, including background conversations and people moving in the lift and obstructing images and map data. It should be noted that the video measurement on Floor A is the uniform distribution, because the information board was obscured by a person walking through the image, meaning no useful information can be extracted.

The Bayesian filter was applied in the same way as for the favourable test, Fig. 9 shows the transit time prediction Fig. 10 illustrates the results. It is clear than when there are disturbances in the lift, the transit time prediction alone would result in the robot incorrectly identifying the floor in the majority of cases. Individually, the additional measurements provide low levels of confidence in the correct floor, but incorporation of all measures produces a much improved estimate.

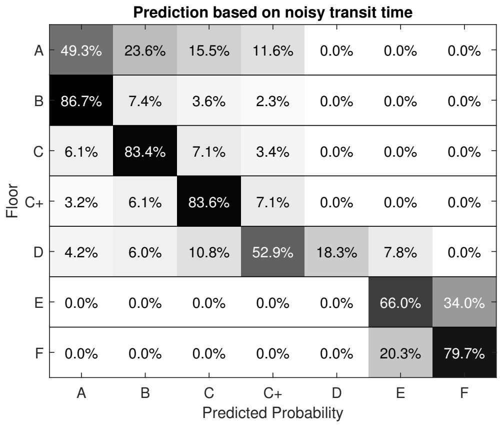

Fig. 9. Floor prediction in adverse conditions

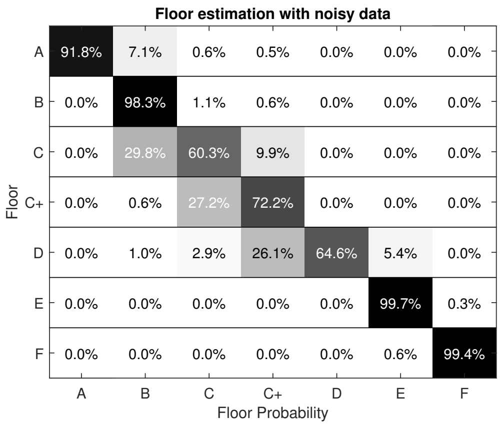

Fig. 10. Floor estimate in adverse conditions

V. Conclusion

This paper has detailed the process by which a mobile guide robot is able to operate a lift with the aid of human bystanders. The robot requests assistance with the operation of the lift, but must be capable of determining when it has arrived on the correct floor such that it may leave in a timely fashion.

It has been shown that, by taking a number of different environmental measurements both in and immediately adjacent to the lift, an autonomous robot is able to correctly determine its floor with high levels of confidence. This ability has been demonstrated in both ideal circumstances, with no obstacles or noise in the environment and in a more challenging situation where all measurements were degraded.

By using a Bayesian filter to combine the various measurements, the robot is not only able to predict which floor it is on but also know its level of confidence in this prediction. With knowledge of this confidence it is possible for the robot to seek further human assistance [2] in the event that it is unsure which floor it is on, for example this may take the form of asking a bystander to confirm the floor.

This paper has solved a key problem in the deployment of autonomous guide robots within a multistory building environment design for humans. With the ability to navigate a lift, further development is now needed of the additional autonomous features required by an autonomous guidance robot such as navigation in close proximity to humans and the elicitation of the necessary assistance from bystanders.

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